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Joint Optimization Scheme for the Planning and Operations of Shared Autonomous Electric Vehicle Fleets Serving Mobility on Demand

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Authors

Sheppard, Colin JR
Bauer, Gordon S
Gerke, Brian F
[et al.](#)

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1 **A JOINT OPTIMIZATION SCHEME FOR THE PLANNING AND OPERATIONS OF**
2 **SHARED, AUTONOMOUS, ELECTRIC VEHICLE FLEETS SERVING MOBILITY ON**
3 **DEMAND**

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7 **Colin J.R. Sheppard**

8 **Gordon S. Bauer**

9 **Brian F. Gerke**

10 **Jeffery B. Greenblatt**

11 **Alan T. Jenn**

12 **Anand R. Gopal**

13

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1 ABSTRACT

2 As the transportation sector undergoes three major transformations — electrification, shared/on-
3 demand mobility, and automation — there are new challenges to analyzing the impacts of these
4 trends on both the transportation system and the power sector. Most models that analyze the re-
5 quirements of fleets of shared, automated, electric vehicles (SAEVs) operate at the scale of an ur-
6 ban region, or smaller. We formulate a quadratically constrained, quadratic programming problem
7 designed to model the requirements of SAEVs at a national scale. We treat as decision variables
8 the size of the SAEV fleet, the necessary charging infrastructure, the fleet charging schedule, and
9 the dispatch required to serve demand for trips in a region. By minimizing both the amortized cost
10 of the fleet and chargers as well as the operational costs of charging, we can explore the coupled
11 interactions between system design and operation. To apply the model at a national scale, we
12 simplify key complications about fleet operations; but we leverage a detailed agent-based regional
13 simulation model to parameterize those simplifications. We present preliminary results finding that
14 all mobility in the United States currently served by 276 million personally owned vehicles could
15 be served by 12.5 million SAEVs at a cost of \$0.27/vehicle-mile or \$0.18/passenger-mile. The en-
16 ergy requirements for this fleet would be 1142 GWh/day (8.5% of 2017 U.S. electricity demand)
17 and the peak charging load 76.7 GW (11% of U.S. power peak). We also explore several model
18 sensitivities and find that sharing is a key factor in the analysis.

19

20 *Keywords:* Electric Vehicles, Vehicle Grid Integration, Shared Mobility, Connected and Autonomous
21 Vehicles

1 INTRODUCTION

2 The transportation sector represents the fastest-growing segment of the world's greenhouse gas
3 (GHG) emissions, with cars accounting for 8.7% of global energy-related carbon dioxide emissions
4 in 2013, and car sales set to more than double by 2050 (1). In 2017, the transportation sector
5 became the largest emitter of greenhouse gases in the United States, overtaking emissions from the
6 electric power industry (2). Transportation, therefore, represents one of the primary challenges to
7 achieving deep decarbonization of the U.S. economy (3, 4).

8 Plug-in electric vehicles (PEVs) have emerged as a market-ready technology with the po-
9 tential to dramatically reduce the carbon intensity of private transportation (5, 6). Prior research has
10 proven the capability of PEVs to meet the travel needs of the majority of drivers in the U.S.(7, 8).
11 Nine U.S. states (California, Connecticut, Maryland, Massachusetts, New Jersey, New York, Ore-
12 gon, Rhode Island and Vermont) have established zero-emission vehicle mandates which combined
13 will lead to deployment of 12 million vehicles, mostly PEVs, in the US by 2030 (9–11).

14 Simultaneously, other important trends are emerging in the transportation sector. This study
15 attempts to align these trends in a coupled evaluation of electric vehicles with shared, autonomous
16 on-demand mobility services. In the remainder of the introduction, we examine future trends
17 in transportation and discuss their potential impact on electrification followed by an overview of
18 analytical approaches that have been employed to model PEV usage which we draw upon for this
19 work.

20 Future trends in transportation

21 *Automation and Shared Mobility*

22 The transportation sector is transforming through the introduction of on-demand mobility and
23 through vehicle automation(12). Increased use of smartphone-enabled shared mobility services
24 through transportation network companies (TNCs) such as Uber and Lyft, are already implicated
25 in reductions in private vehicle ownership (13). Automation, too, may result in significant changes
26 in how people use vehicles and their associated energy consumption. Self-driving vehicles are
27 already on the roads, serving passengers in the United States without a human backup driver in
28 the vehicle (14). Synergy among these "three revolutions" (15, 16) could result in deep GHG
29 reductions (17).

30 However, adoption of PEVs has been relatively slow for several reasons, including techno-
31 logical uncertainty, slow charging, range anxiety, and higher capital costs compared to other types
32 of vehicles(18, 19). The leading developer of vehicle automation technology, Waymo, has entered
33 an agreement to purchase 20,000 PEVs by 2020 (20). While there is still a great deal of uncer-
34 tainty around the impact that automated vehicles (AVs) will have on the transportation system in
35 the coming decades (21, 22), there is little doubt that they will soon be a part of the transportation
36 system and could dramatically disrupt conventional modes of mobility. There are a wide variety of
37 business models that could make use of AVs (23). The success of these business models will de-
38 pend on their relative cost structures (24), regulatory burden (25), consumer acceptance (26), and
39 a host of other factors. However, there is growing consensus that without sharing rides, i.e., more
40 than one passenger per vehicle, the end result of vehicle automation could increase undesirable
41 outcomes like vehicle miles traveled, congestion, energy consumption, and emissions (16, 27, 28).

42 Shared, automated electric vehicles (SAEVs)(29) could offer on-demand transportation in
43 electric and self-driving cars similar to the service provided by current TNCs but likely at much
44 lower cost and carbon intensity. Because each SAEV need only have enough seats (known as

1 "right-sizing") and battery range for the trip requested and charging can be split over many short
2 periods in between trips, the shared mobility paradigm could enable the use of smaller cars with
3 shorter battery range, thus overcoming the barriers of slow charging speed and high capital cost (17,
4 30, 31).

5 Furthermore, because shared vehicles typically travel many more miles annually than pri-
6 vate vehicles, deployment of SAEVs would increase the per-vehicle GHG reductions relative to
7 private ownership and spread the capital costs over more miles. SAEVs deployed in 2030 could
8 reduce GHG emissions per mile by more than 90% relative to privately-owned conventional ve-
9 hicles while substantially increasing cost-effectiveness (17). A recent Rocky Mountain Institute
10 report predicted that the marginal cost of SAEVs could fall below that of conventional private ve-
11 hicles leading to market dominance by 2050 (32). It is possible that such cost savings will increase
12 overall vehicle miles traveled as a result of induced demand, but some studies have predicted that
13 the efficiency gains would outweigh any resulting potential increases in emissions (12).

14 *Charging Infrastructure and Vehicle Grid Integration*

15 Public PEV charging infrastructure is a critical component to accelerate the adoption of PEVs (33–
16 35), however there is a weak business case for the private sector to invest in chargers in the context
17 of personally owned PEVs (36). Governments across the world have therefore initiated campaigns
18 to support the planning and installation of charging infrastructure to varying degrees (11, 37–40).

19 PEV charging introduces a significant new load to an electric system that is already chal-
20 lenged to meet peak electricity demand multiple times each year, as well as incorporate increasing
21 levels of intermittent wind and solar generation. As intermittent renewable capacity increases, the
22 incidence of renewable energy (RE) curtailment increases which raises the overall system cost of
23 supplying electricity (41). In addition, some utilities must meet a renewable energy production
24 standard to satisfy regulatory mandates, so renewable curtailment forces them to either acquire
25 more RE or introduce sources of grid flexibility to relieve the curtailment (42).

26 Many studies have assessed the benefits of coordinated PEV charging on electric power
27 system operations, (43–45). If charging is properly coordinated, it can provide a dual benefit of
28 decarbonizing transportation while lowering the capital costs for widespread renewables integra-
29 tion and reducing the need for energy storage (46–49). The capability of PEVs to enhance the
30 integration of renewable energy sources, including wind (50–55) and solar, (56–61) into the exist-
31 ing power grid has been widely discussed.

32 **Analytical Approaches**

33 PEVs models typically fall into two groups: trip-based models and activity-based models. Trip-
34 based models typically summarize or infer travel patterns from travel survey data and use them
35 to characterize the need for PEV charging infrastructure and the temporal opportunities to charge
36 (62–64). Such approaches cannot account for the individual mobility constraints of travelers and
37 they typically require an assumption that charging infrastructure is unlimited.

38 The most common form of activity-based PEV models make use of travel diaries from
39 surveys or GPS data logging which are then provided as input to energy and charging simulations
40 that estimate the energy consumption and state of charge of a PEV batteries and therefore the
41 necessity or propensity to recharge at the conclusion of trips (65–68).

42 Agent-based models — a subset of activity-based models — treat travelers individually and
43 require a representation of each individual's activity schedule in order to model the travel neces-

1 sary to engage in those activities. Several previous studies have employed agent-based modeling
 2 techniques to explore the feasibility of a fleet of automated taxis operating in an urban environ-
 3 ment (24, 29, 69–74). Building on these results, Bauer et al. (31) developed an agent-based model
 4 to predict the system costs of a fleet of SAEVs operating in New York City (NYC) and design a
 5 heuristic process to size the fleet and dispatch the vehicles to serve demand that is derived from
 6 trip data or stochastically created. We refer to this model as the Bauer, Greenblatt, Gerke (BGG)
 7 model.

8 Previous studies have shown that electric taxi fleets are viable options under certain cir-
 9 cumstances. However, those studies have chosen fixed values for various fleet parameters. To our
 10 knowledge, Bauer et al. (31) was the first study that explores a variety of vehicle, operational, and
 11 infrastructure parameters to identify the fleet configuration with lowest cost, and the corresponding
 12 environmental and energy impacts. It also assumed that taxis can relocate to charge whenever they
 13 are idle, which may reduce both the required battery range and overall cost as well as the impact
 14 of the vehicle fleet on the power grid.

15 In this work, we use a hybrid analytical approach. We develop a trip-based optimization
 16 model that can scale to a national scope and we develop key assumptions and parameters for this
 17 trip-based model by applying the BGG model in nine urban regions.

18 **APPROACH**

19 The primary contribution of this analysis is the optimization model. This model treats the size of
 20 the PEV fleet and the amount of charging infrastructure as continuous decision variables (relax-
 21 ing the problem from mixed-integer to quadratic), allowing for heterogeneous vehicle ranges and
 22 charger levels. The model minimizes operational costs by choice of the timing of fleet recharging
 23 while requiring that mobility demand be served and energy conserved. Planning costs are simul-
 24 taneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily time
 25 period. For a full model specification, see Section "Model Specification".

26 In addition to developing the optimization model, we also curated a set of empirically-
 27 derived inputs and assumptions for the model application. While more work is needed to refine
 28 the model and assumptions (see Section "Gaps and Shortcomings"), we believe that useful insights
 29 can already be gleaned from the results of the modeling workflow. These are discussed in detail in
 30 Section "Results and Discussion".

31 In Figure 1, we illustrate the source of all major model inputs and assumptions including
 32 intermediate modeling and analysis used in their derivation. Each model input is described in
 33 further detail below, beginning with the specification of the optimization model.

34 **Model Specification**

35 The dimensions of the model include time, t , region r , vehicle battery size b , charger level l , and
 36 trip distance d . The model is quadratic in the objective as well as the constraints and therefore can
 37 be efficiently solved with a second-order cone programming solver.

38 *Objective*

The objective is to minimize the amortized daily cost of the fleet, the infrastructure, and of fleet operations.

$$\min Z = \sum_r \left(\sum_t C_{tr} + I_r^c + I_r^v \right) \quad (1)$$

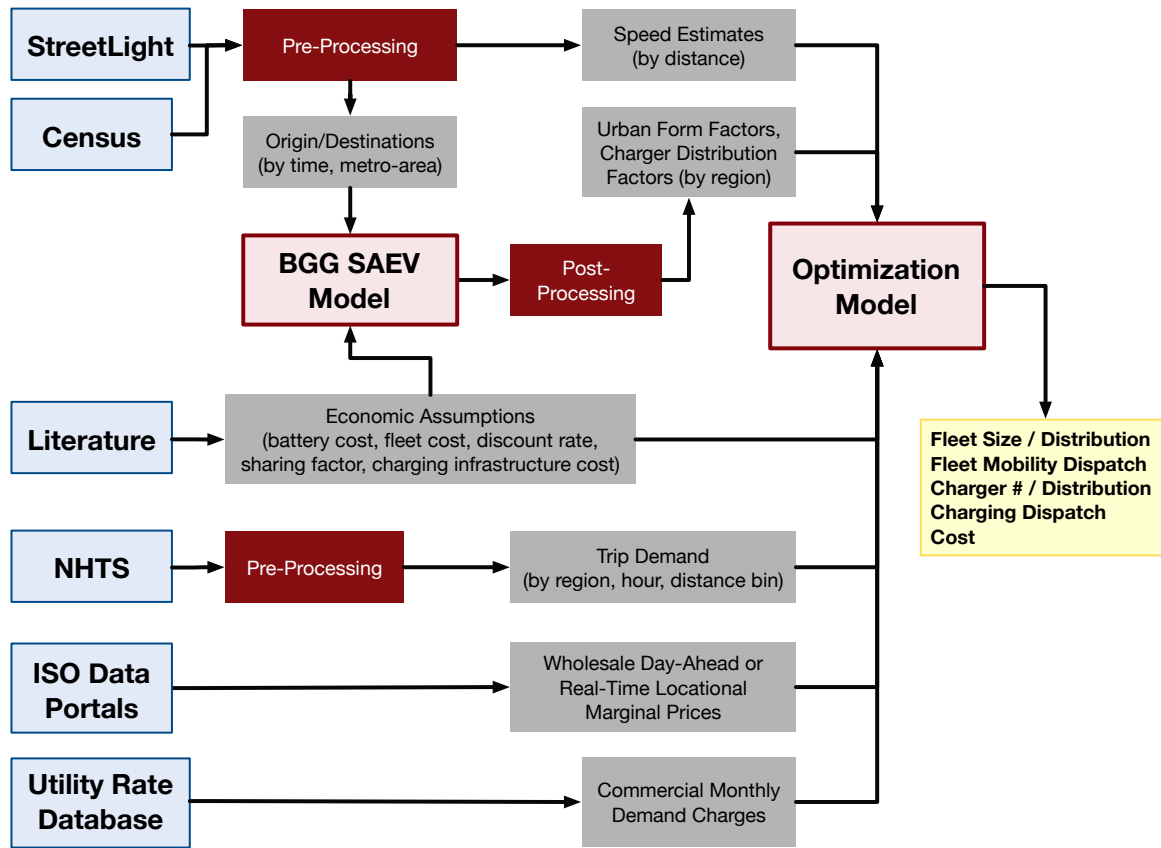


FIGURE 1 Sources of data (blue), data processing (dark red), models (light red), intermediate data (grey), and model outputs (yellow) in the overall modeling and processing workflow.

1 Where C_t is the operations cost in hour t and region r , I_r^c is the amortized daily charging
 2 infrastructure cost, and I_r^v is the amortized daily fleet cost.

3 *Constraints*

4 **Operations Cost:** cost of electricity energy and capacity, as well as mileage-dependent vehicle
 5 maintenance.

$$C_{tr} = \sum_b \left(\sum_l P_{btlr} \tau_{lr} + \beta_v \sum_d \rho_d D_{bdtr} \right) + P_r^{max} \beta_r / N_T \quad (2)$$

6 Where P_{btlr} is the energy dispensed for charging by vehicle class b in time t using level l
 7 in region r , τ_{lr} is electricity price (\$ / kWh), β_v is the per-mile vehicle maintenance cost, ρ_d is the
 8 average travel distance in miles per passenger trip for distance bin d , D_{bdtr} is the allocated demand
 9 for trips, P_r^{max} is the maximum power demanded over the time horizon, β_r is the average demand
 10 charge for the region (\$/kW/day), and N_T is the number of time steps in the simulation (this turns
 11 the demand charge which is levied once per day into an hourly cost). In reality, demand chargers

1 are usually levied on a monthly basis, so this daily charge neglects the fact that day to day variation
 2 would likely lead to a higher monthly payment than a simulation based on a single day. This can
 3 be compensated for through sensitivity analysis or increasing the number of simulated days, a task
 4 for future work.

5

6 **Infrastructure Cost:** in this constraint, the charger distribution factor accounts for spatial mis-
 7 match between vehicle locations and available charger locations as well as overbuilding necessary
 8 to decentralize chargers. In other words, for a given number of vehicles charging, we require ad-
 9 ditional charging infrastructure assuming that not all chargers are sited in the right location at the
 10 right time.

$$I_r^c = \sum_l N_{lr} \gamma_l \delta_l \theta_l^c \quad (3)$$

11 Where δ_l is the charger distribution factor, γ_l is the power capacity of the charger (kW),
 12 and θ_l^c is the amortized daily charger cost (\$/kW):

$$\theta_l^c = \frac{\phi_l^c r (1+r)^{L^c}}{(1+r)^{L^c} - 1} \quad (4)$$

13 Where ϕ_l^c is the capital cost of charger of level l , L^c is the lifetime of the charger in days,
 14 and r is the daily discount rate.

15

16 **Fleet Cost:** in this constraint, battery costs are considered separately from the rest of the vehi-
 17 cle.

$$I_r^v = \sum_b V_{br}^* (\theta^v + \theta^b B_b) \quad (5)$$

18 Where V_{br}^* is the fleet size, θ^v is the amortized daily vehicle cost (without a battery), θ^b is
 19 the amortized daily battery cost (\$/kWh), B_b is the battery capacity (kWh).

$$\theta^v = \phi_{om}^v + \frac{\phi^v r (1+r)^{L^v}}{(1+r)^{L^v} - 1} \quad (6)$$

$$\theta^b = \frac{\phi^b r (1+r)^{L^b}}{(1+r)^{L^b} - 1} \quad (7)$$

20 Where ϕ_{om}^v is the daily variable O&M cost for the vehicle, ϕ^v is the capital cost of the ve-
 21 hicle, and L^v is the lifetime of the vehicle in days. And where ϕ^b is the capital cost of the battery
 22 (\$/kWh) and L^b is the lifetime of the battery in days.

23

24 **Energy to Meet Demand:** the energy consumed by the fleet is a function of the number of trips

1 served, the conversion efficiency of the vehicles, the urban form (which determines the length of
 2 empty vehicle trips) and ride sharing. We model the effect of urban form and sharing as multipliers
 3 on the energy efficacy of serving mobility demand.

$$E_{bdr} = \frac{D_{bdr} \mu_r \eta_b \rho_d}{\sigma_d} \quad (8)$$

4 Where E_{bdr} is the energy consumed serving mobility of vehicle type b and trip length d in
 5 hour t and region r , σ_d is the sharing factor or the average number of passengers per vehicle trip,
 6 μ_r is the urban form factor or one plus the ratio of empty vehicles miles driven to vehicle miles
 7 driven with passengers, and η_b is the conversion efficiency of the vehicle power train (kWh/mile).
 8

9 **Vehicles Moving:** the number of vehicles actively serving trips is related to trip demand and the
 10 sharing factor. The term $\frac{\rho_d}{\Delta t v_{dtr}}$ corrects for the length of the time period, allowing, e.g. 1 vehicle to
 11 serve 2 trips in an hour if the distance to speed ratio is 1/2.

$$V_{bdr}^m = \frac{D_{bdr} \rho_d}{\sigma_d \Delta t v_{dtr}} \quad (9)$$

12 Where V_{bdr}^m is the number of vehicles of type b serving mobility demand of trip length d in
 13 hour t and region r , v_{dtr} is the average velocity of vehicles, and Δt is the length of the time period
 14 in hours.
 15

16 **Vehicles Charging:** we relate the number of vehicles charging to the power consumed by the
 17 capacity of each charger type.

$$V_{btr}^c = \frac{P_{btr}}{\gamma_t} \quad (10)$$

18 Where V_t^c are the number of vehicles charging in hour t , and γ_t is the charging rate (kW /
 19 charger).
 20

21 **Charging Upper Bound:** we assume the batteries in fleet start full and therefore can only be
 22 replenished up to the cumulative amount consumed by the previous hour.

$$\sum_{i=0}^t \sum_l P_{b\hat{i}lr} \leq \sum_{i=0}^{t-1} \sum_d E_{b\hat{i}lr}, \quad \forall btr \quad (11)$$

23
 24 **Charging Lower Bound:** charging must keep up with consumption as limited by the capacity
 25 of the batteries. Energy must be supplied by charging in the previous hour to be used in the
 26 next hour. This constraint prevents the aggregate state of charge of the vehicles from becoming
 27 negative. By constraining only the aggregate state of charge and not constraining individual vehicle
 28 states of charge, we are assuming that the fleet can be managed to maintain all individual vehicles

1 appropriately. In practice there could be solutions to the aggregate problem that are challenging to
 2 satisfy with the individual vehicles.

$$\sum_{\hat{t}=0}^{t-1} \sum_l P_{b\hat{t}lr} \geq \sum_{\hat{t}=0}^t \sum_d E_{bd\hat{t}r} - V_{br}^* B_b, \quad \forall btr \quad (12)$$

3

4 **No Charge At Start:** the first hour of the day needs to have no charging to allow for the convention
 5 that charging can only occur after some energy is consumed by the fleet.

$$P_{btlr} = 0, t = 0, \quad \forall btr \quad (13)$$

6

7 **Terminal State of Charge:** the aggregate state of charge of batteries must again be full at the end
 8 of the day. This constraint would be too restrictive if the end of the day is defined as midnight
 9 (since there is still a fair amount of VMT during that hour). We therefore shift our day boundary
 10 to the lowest VMT level of the day, which typically occurs at 4am.

$$\sum_t \sum_l P_{btlr} = \sum_t \sum_d E_{bdtr}, \quad \forall br \quad (14)$$

11

12 **Demand Allocation:** demand must be served by some composition of vehicles.

$$\sum_b D_{bdtr} = DD_{dtr} \quad (15)$$

13

Where DD_{dtr} is exogenous demand in hour t (person trips).

14

15 **Fleet Dispatch:** together vehicles serving trips, charging, and idle cannot exceed the fleet size.

$$\sum_d V_{bdtr}^m + V_{btr}^i + \sum_l V_{btlr}^c \leq V_{br}^* \quad (16)$$

16

17 **Max Charging:** vehicles charging cannot exceed the number of chargers.

$$\sum_{bd} V_{bdtl}^c \leq N_{lr} \quad (17)$$

18

Where N_{lr} is the number of chargers charging at power level l in region r .

19

20 **Max Demand:** this constraint relates the maximum power consumed for each region to the power
 21 drawn in each time period. Because P_r^{max} is in the objective function, there will be no slack in the
 22 optimal solution, ensuring it will be equal to the maximum power demanded by the fleet.

$$P_r^{max} \geq \frac{\sum_{bl} P_{tblr}}{\Delta t}, \quad \forall tr \quad (18)$$

1 **NHTS Data**

2 We applied the model at a national level based on estimates of hourly demand for private vehicle
3 trips on a typical day, as derived from the 2017 National Household Transportation Survey (NHTS)
4 (75). NHTS respondents log trip distance, timing, and vehicle type for all household members on
5 a specified day. The responses are weighted according to demographics to yield a typical mobility
6 profile over a single day across the United States.

7 To produce our trip-demand model inputs, we partitioned the country into thirteen broad
8 geographic regions, made up of the nine US Census Divisions,¹ with the four largest states (Califor-
9 nia, Florida, New York and Texas) separated out into their own individual regions². Hereafter, we
10 refer to these regions interchangeably as "regions" or as the Census-Division-Large-State (CDLS)
11 subdivision. In addition, we subdivided the trips according to an NHTS data field that specifies
12 whether a given respondent is in an urban or a rural area. This yields a total of 26 regional data sets
13 (thirteen CDLS regions, each with urban and rural subregions). Within each region, we take all
14 trips in private vehicles,³ and compute weighted counts in eight bins of trip distance⁴, with counts
15 computed independently for typical weekdays and weekend days. This specifies the distribution
16 of total daily trip demand by trip distance within each region.

17 To investigate the dynamics of vehicle charging and the related effects on the grid, we must
18 also estimate the time variation of trip demand throughout the day. One straightforward approach
19 would further subdivide the regional and distance bins by hour to produce hourly distributions of
20 trip demand by distance. However, the NHTS dataset is insufficiently large to support this level
21 of granularity without introducing substantial noise into the trip demand estimates, especially for
22 longer trips and less populous regions. To circumvent this issue, we separately computed hourly
23 trip distributions (by the hour in which the trip initiated) for each distance bin, subdivided by
24 urban vs. rural and weekday vs. weekend, but aggregated up to the entire United States, rather
25 than subdivided by CDLS. We then apply these hourly trip distributions to the total trip counts
26 computed within the more granular CDLS regions to produce estimates of the hourly trip volume
27 by distance within each region. The resulting hourly trip distributions thus capture geographical
28 variations in overall trip volume at the detailed CDLS level, while assuming regional differences
29 in the hourly profile of trip demand are insignificant (indeed, disaggregating this calculation into
30 the four US census regions showed regional differences that were noisy but consistent). Figure 2
31 shows the resulting trip distributions.

32 **StreetLight Data**

33 In order to determine realistic values for urban form factor and charger distribution factor for the
34 optimization model, we coupled trip data obtained from StreetLight Data with the BGG model.
35 StreetLight Data is a company that aggregates data from cell phones and GPS devices to produce
36 transportation metrics like travel times and volumes.

37 First, we obtained shapefiles from the Census Bureau website with census tracts for a se-
38 ries of combined statistical areas, as shown in Table 1. We then uploaded these shapefiles to the
39 StreetLight Data portal, and obtained two types of data. "Trip attributes" files contained distances,

¹These are New England (NE), Mid-Atlantic (MAT), South Atlantic (SAT), East-North-Central (ENC), West-North-Central (WNC), East-South-Central (ESC), West-South-Central (WSC), Mountain (MTN) and Pacific (PAC).

²we use "NL" to refer to the remainder of the divisions containing the large states, "NL" stands for "Not Large"

³specifically, the following NHTS vehicle type codes: car, SUV, van, pickup truck, motorcycle, RV, and rental car.

⁴mileage intervals specified by (0, 2], (2, 5], (5, 10], (10, 20], (20, 30], (30, 50], (50, 100], and (100 – 300]

URBAN WEEKDAY

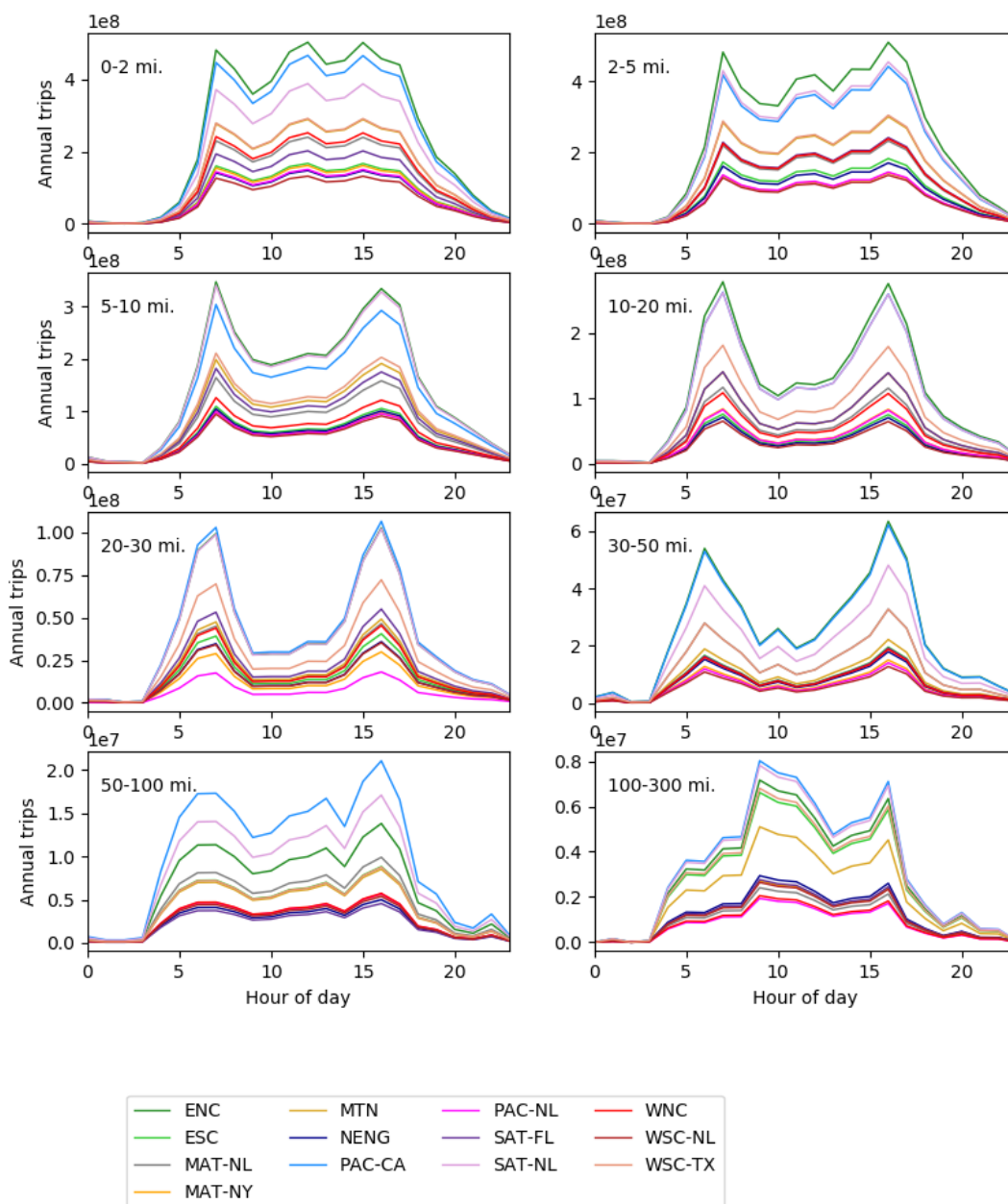


FIGURE 2 Hourly trip distributions (by hour of trip initiation), for weekdays, in bins of trip distance, as estimated from the 2017 NHTS for urban areas in 13 CDLS geographic regions.

1 times and speeds between each pair of census tracts. Data was only provided for zone pairs with
 2 a significant number of trips, as determined by StreetLight Data. "Trip Counts" data contained
 3 the volume of trips between each census tract origin and every traffic analysis zone (TAZ) with
 4 a significant volume, again as determined by StreetLight. The data also contained significant trip

1 counts between each origin TAZ and destination census tract.

TABLE 1 Combined statistical areas used for multi-city simulations with the BGG model.

Name	Area (1000 km^2)	Census Division	Population (1000s)
Buffalo-Cheektowaga, NY	7.4	New York	1214
Charleston-Huntington-Ashland, WV-OH-KY	13.8	South Atlantic	680
Dallas-Fort Worth, TX-OK	42.7	Texas	7846
Fort Wayne-Huntington-Auburn, IN	8.2	East North Central	631
Lafayette-West Lafayette-Frankfort, IN	4.4	West South Central	252
Martin-Union City, TN-KY	3.4	East South Central	70
Rockford-Freeport-Rochelle, IL	5.5	East North Central	434
Seattle-Tacoma, WA	31.8	Pacific	4765
Virginia Beach-Norfolk, VA-NC	10.8	South Atlantic	1829

2 Since Streetlight trip attributes were binned into larger intervals (e.g. percent trips with
3 durations between 10-20 minutes, or 5-10 miles), the first processing step was to interpolate dis-
4 tributions with increased resolution, binning distributions by 1 min, 0.1 mi, and 1 mile per hour
5 for trip duration, distance, and speed, respectively. To interpolate missing values, we found the
6 average distributions from the three nearest zones, along with data from the nearest zones in the
7 hour before and after. This process was repeated iteratively until over 99% of all O-D pairs had
8 data in all hours for all three attributes.

9 While this interpolation process introduces a source of error into our model, we consider it
10 acceptable for two reasons: all trip data between census tracts comes from zone pairs with actual
11 data, and in previous work Bauer et al. (31), we found that modifying trip relocation times by
12 distributions with mean zero did not significantly change our results.

13 Trip counts were binned by hour, so we interpolated the data to estimate the number of trips
14 starting in each minute. Trips starting outside of the CSA were removed to avoid double-counting
15 trips between regions.

16 These pre-processing steps resulted in trip counts for each origin-destination pair by minute,
17 and distributions of duration, distance, and speed for each origin-destination pair by hour. We used
18 this data as input for the BGG model.

19 The BGG model proceeds chronologically over one day of data, repeating until the fleet's
20 aggregate battery capacity at the end of the day is within 5% of that at the beginning of the day.
21 In each minute, trips are assigned to the nearest vehicle, and idle vehicles are routed to charge or
22 rebalanced in anticipation of future demand (31). Travel times and distances between each taxi and
23 trip or charging point are imputed by drawing random values from the corresponding distribution
24 obtained from StreetLight Data. To ensure a reasonable relationship between time, distance, and
25 speed for each trip, distances are re-sorted in order to best match the relationship between draws
26 for duration and speed. If a trip can only be served by a vehicle with insufficient battery capacity,
27 the vehicle's range is increased by 50-mi increments until capacity is adequate. If no vehicle can
28 serve a trip within a 10-min wait time, a new vehicle is added to the fleet. Thus, both battery range
29 and fleet size increase organically over the course of the simulation, providing estimates of the

1 minimum values required to serve demand.

2 Simulations were conducted for each city with 100k, 200k, 400k, and 800k trips, and with
3 both 15kW and 50kW charging power. Locations of chargers were determined by k-means clus-
4 tering of trip origins and destinations, which was determined to work as effectively as the siting
5 algorithm described in Bauer et al. (31). Simulations were then run with sufficient chargers to
6 recharge the fleet assuming 25% empty miles and 50% charger utilization, then again assuming
7 100% charger utilization. In each case, every charger was occupied during peak charging times, so
8 we concluded that a charger distribution factor δ_i of 1 would be sufficient.

9 While the simulation ran, we recorded the empty distance traveled for each trip and charg-
10 ing event, and aggregated across census tracts to determine the urban form factor μ_r in both rural
11 and urban areas of each city. Following the definition used by NHTS, rural areas were considered
12 to be all census tracts within a CSA not contained within an urbanized area or urban cluster, as de-
13 termined by the Census Bureau. As shown in Figure 3, we found that urban form factor increases
14 roughly with the square root of area per trip. Using ordinary least squares regression techniques,
15 we extrapolated these ratios to all other CSAs and urbanized areas in the country based on popula-
16 tion and area. Finally, we took population-weighted means to extrapolate from cities to determine
17 the urban form factor for each census division.

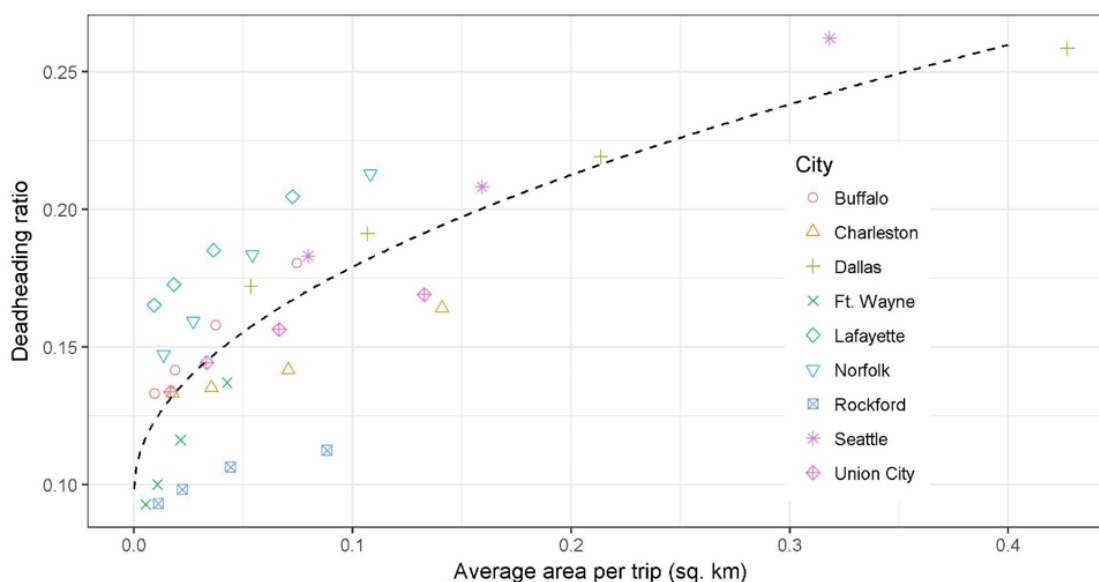


FIGURE 3 Ratio of empty miles to passenger miles in each simulated CSA versus the ratio of CSA land area to number of trips, with square-root regression line.

18 Power Sector Data

19 In order to model the fleet operations with reasonable electricity cost estimates, we developed
20 different pricing scenarios that vary over a range of potential economic conditions on the grid.
21 We downloaded real time locational marginal price data (or, if unavailable, day ahead price data)
22 from five Independent System Operators (ISOs) across the United States. The ISOs were CAISO,
23 NYISO, PJM, ERCOT, and MISO. Data were downloaded for the entire year of 2017 as well as
24 the first half of 2018. Across all five ISOs and all locational pricing nodes, we took the median

1 price from each hour of the day across the entire data set. In addition, we took median prices for
2 each combination of ISO and month and used some of the resulting price profiles in one sensitivity
3 analysis (Section "Price Shape"). We then subtracted the average of the price profiles and added
4 \$0.09/kWh to produce a price shape that keeps the hourly variation in price from the wholesale
5 sector, but has an average daily price equivalent to the average commercial retail electricity rate
6 in the U.S. as estimated by the Energy Information Agency (76). This hybrid approach allows the
7 overall cost to reflect the end-user cost of purchasing electricity while also allowing the fleet to
8 take advantage of price arbitrage opportunities throughout the day. The loads from these fleets will
9 be very large in aggregate, so it is reasonable to expect they will somehow be able to participate in
10 wholesale power markets.

11 The final price assumption for the base scenario is shown in Figure 4 along with 4 other
12 pricing scenarios. The "CAISO-Duck" scenario is based on the California median price of elec-
13 tricity in March, 2017; the "ERCOT-Summer" scenario is based on Texas prices in July, 2018, and
14 the "NYISO-Winter" scenario is based on New York in January, 2018.

15 Based on data from the Utility Rate Database (77), we estimated a median national re-
16 tail rate for demand charges in the U.S. We subsetted the data to commercial rate schedules and
17 then took the demand charge price from the primary monthly period (i.e. if multiple time-of-use
18 periods are defined, we only used the first period in the database) and found the median to be
19 \$7.7/kWh/month. The interquartile range was from \$3 to \$10.7, demonstrating substantial vari-
20 ability in prices nationwide. We found however, that model results are largely insensitive to this
21 assumption.

22 **Key Assumptions**

23 In Table 2, we list all key assumptions used for the Base scenario of the optimization model.

24 **Gaps and Shortcomings**

25 There are several gaps in the model specification and assumptions that should be kept in mind
26 when considering model results. In future research many of these shortcomings will be addressed.

- 27 • This model is only concerned with the distant hypothetical future where SAEVs are a
28 dominant mode of transportation. In future work, we will add personally owned EVs and
29 their respective impact on vehicle grid interactions to the model in order to analyze the
30 transition to such a future.
- 31 • Price is exogenously defined. In reality, the load and charging flexibility of a SAEV fleet
32 would be enough to influence the cost of generating power. In future work we will make
33 power production costs endogenous to the model.
- 34 • Mobility demand is exogenously defined. In reality, demand for mobility responds to the
35 cost, travel time, and convenience of the transportation alternative both when competing
36 against other modes but also with respect to long term shifts in land use and travel pat-
37 terns. In future work we will more closely align our demand assumptions with detailed
38 regionally travel demand analyses that do account for these feedbacks.
- 39 • The time used across all of the regions is in local time. While this should not impact the
40 dynamics of fleet dispatch to serve mobility, the resulting charging profiles are inappro-
41 priately assumed to be additive by hour.
- 42 • The mobility assumptions only cover a typical weekday, a more accurate planning model
43 would include weekend/holiday in the model and weight the operational costs of these

TABLE 2 Key modeling assumptions used to define the Base scenario.

Input	Symbol	Value(s)
Charger Types and Power	γ_i	L010=10kW, L020=20kW, L050=50kW, L100=100kW, L250=250kW
Charger Capital Cost	ϕ_l^c	L010=\$5k, L020=\$11k, L050=\$35k, L100=\$95k, L250=\$425k
Charger Lifetime	L^c	10 years
Charger Distribution Factor	δ_l	1.0 for all types
Demand Charge Price	β_r	\$7.7/kW/month
Energy Price	τ_{tr}	See Figure 4
Annual Discount Rate	r	0.05
Number of Distance Bins	$Card(d)$	10
Urban Form Factor	μ_r	See Figure 10
Sharing Factor	σ_d	1.5
Vehicle Capital Cost	ϕ^v	\$30,000 (includes cost of automation)
Vehicle Daily Fixed O&M	ϕ_{om}^v	\$0.64
Vehicle Per-Mile O&M	β_v	\$0.09
Battery Capital Cost	ϕ^b	\$150/kWh
Vehicle/Battery Lifetime	L^v, L^b	3.4 years
Battery Capacity	B_b	75mi range=19.7kWh, 150mi range=41.1kWh, 225mi range=64.4kWh, 300mi range=89.4kWh, 400mi range=124.0kWh
Conversion Efficiency	η_b	75mi range=0.262kWh/mi 150mi range=0.274kWh/mi 225mi range=0.286kWh/mi 300mi range=0.298kWh/mi 400mi range=0.310kWh/mi
Speed by Distance Bins	v_{dtr}	1.1 to 3.6mi = 18mph, 13.4 to 14.1mi = 32mph 24.1mi = 38mph, 35.5mi = 40mph 60.3 to 69.6mi = 45mph, 159.9mi = 48mph

1 days to produce an annualized cost.

- 2 • The speed distributions are exogenous and fixed, we therefore are ingoring the impact of
3 congestion on travel times. This is a major feedback that can only be addressed through
4 more extensive use of detailed travel demand models that simulate traffic flow.
5 • Electricity price is based on a median price and the simulation only runs for one day.
6 Electricity prices are highly variable by day and season. An improved model would
7 include multiple days in the simulation representative of a full year.
8 • The model does not consider temporal overheads associated with charging (e.g. maneu-
9 vering to spot, plugging in, etc.) and with maintenance (e.g. cleaning the vehicle inte-

rior). These processes could be approximated by derating the charging power associated with each charger level.

- The model ignores the impact of C-rate and battery degradation on system cost and performance. In particular, we ignore the fact that in high power charging, the charging rate must be reduced past a vehicle state of charge of 80% before charging can commence.
- The model ignores the difference in battery lifetime among vehicles with different sized batteries. These would not age at the same rate, and should therefore be disaggregated.
- The model does not attempt to optimize the seating capacity of the vehicles.
- We neglect medium/heavy duty vehicle electrification that will likely take place along with passenger vehicle PEVs and have impacts on aggregate electricity consumption and peak load.
- We assume a constant sharing factor across the model, but it likely varies by region, trip distance, and time of day.
- We estimate the variability of urban form factor by region, but it likely also varies by trip distance and time of day.
- We neglect the cost of parking. This is due primarily to the challenge of estimating regional average parking costs in addition to the fact that under a high penetration SAEVs, parking would become much less limited in general, making current parking prices unrepresentative of future costs.

RESULTS AND DISCUSSION

In light of the gaps described above, we present the preliminary results of running the model for the entire United States. These results should be interpreted as generally indicative of the characteristics of a national SAEV fleet, not as a high-confidence prediction.

Base Scenario

We present high level summary metrics for the cost minimizing configuration of vehicle fleet, charging infrastructure, and charging profiles resulting from the Base scenario in Table 3 at both the national and regional scales.

If all U.S. mobility were satisfied by SAEVs with a sharing factor of 1.5, a fleet of only 12.5 million vehicles and 2.4 million charge points would be required, consuming 1,142 GWh of energy per day (or 8.5% of daily U.S. electricity demand) with a peak load of 76.7 GW (or 11% of the U.S. non-coincident peak) at a cost of \$0.27/mile. The distribution of power capacities in the charging infrastructure is strongly weighted toward 50kW chargers (Table 3), but the solution includes substantial numbers of lower power chargers as well, roughly split between 10kW and 20kW chargers.

The regionally disaggregated results tend to follow predictable patterns that are closely related to the population of the region, and therefore demand for mobility. When comparing demand for charging in specific regions to current-day electricity demand, the result can be quite different from the national average. For example, the 2017 peak load in CA is 50GW and the simulated charging peak is 6.5GW, or 17% of the current peak. This represents a large increase in load and the management of the fleet charging would be of major consequence to the grid operator.

The distribution of vehicle types and charger power by region are shown in Figure 5. There are clear, systematic differences in fleet composition between urban and rural sub-regions, with a greater reliance on longer range vehicles in the rural areas where trip lengths are longer (12.4 miles

1 on average versus 7.8 for urban). The charging infrastructure requirements in rural regions often
2 include 100kW chargers while the urban regions can be satisfied by lower power chargers.

3 In Figure 6, the bulk dispatch of the vehicle fleet between moving, charging, and sitting
4 idle is shown over the course of the day. The total size of the fleet is determined by the afternoon
5 peak for mobility demand (4pm rush hour). Despite the steep drop in demand for mobility into the
6 evening hours, overnight charging of the fleet doesn't begin until after midnight (hour 25) taking
7 advantage of the steadily decreasing marginal electricity price (Figure 4).

8 In Figure 7, the daily profile of aggregate energy stored in the batteries of the fleet is shown,
9 disaggregated by vehicle type. The batteries are assumed to start the day full and this energy is
10 used to meet the morning rush hour with some modest recharging in the early hours of the day.
11 After the 7am mobility peak, roughly half of the fleet that is not needed for serving mobility is
12 continuously recharged until the afternoon rush begins at 3-4pm. This charging replenishes the
13 energy in the fleet sufficiently to allow mobility to be served through the afternoon rush into the
14 late evening with very little charging. We acknowledge that the aggregate state of charge depletes
15 almost to zero which is unlikely to be acceptable to fleet managers. In future analysis we will
16 constrain this lower bound to allow for energy reserves and operational flexibility.

17 Finally, Figure 8 shows the distribution of charging by charger power capacity over the
18 course of the day. During peak charging hours, all chargers are in use. During most of the rest of the
19 day, the distribution of charging is roughly proportional to the charging infrastructure distribution.

20 Also of note in the regional results is the per-mile cost does not vary in a consistent manner
21 between urban vs. rural regions. Vehicle cost is the largest contributor to overall cost (Figure 9).
22 The variation in urban vs. rural regions is therefore largely driven by the composition of the
23 fleet, which ultimately is a result of the particular distribution of mobility demand for each region.
24 Based on a regression analysis, 45% of the variation in the difference in cost between urban and
25 rural regions can be explained by the relative differences in the demand for person trips and for
26 person miles traveled in the regions. The differences in urban form factor between urban and rural
27 regions (Figure 10) were not predictive of the cost results. The other potential explanation for the
28 variation include the timing of mobility, an effect that will be explored in future research.

TABLE 3 Optimal system configuration and operational statistics for the Base scenario.

Division	Region Type	Demand (GWh/day)	Peak (GW)	VMT ($\times 10^6$)	Fleet ($\times 10^3$)	Chargers ($\times 10^3$)	L010 ($\times 10^3$)	L020 ($\times 10^3$)	L050 ($\times 10^3$)	L100 ($\times 10^3$)	% of US Demand	% of US Peak	Cost (\$/mi)
National	All	1142	76.7	3012	12,529	2401	599	680	1102	19	8.5	11	0.266
ENC	Rural	67.2	4.64	176	599	166	91	0	74	0	0.5	0.69	0.246
ENC	Urban	109	7.16	291	1275	232	29	109	93	0	0.81	1.1	0.271
ESC	Rural	43.3	3.05	116	366	99	53	0	40	4	0.32	0.45	0.238
ESC	Urban	45.3	2.99	172	499	86	7	33	44	0	0.34	0.44	0.211
MAT-NL	Rural	15.7	1.1	28	140	41	24	0	17	0	0.12	0.16	0.319
MAT-NL	Urban	51.2	3.33	135	593	106	13	49	44	0	0.38	0.49	0.271
MAT-NY	Rural	12.4	0.868	30	120	30	16	0	14	0	0.092	0.13	0.262
MAT-NY	Urban	34.1	2.26	78	407	69	7	30	31	0	0.25	0.34	0.302
MTN	Rural	20.6	1.41	49	172	40	21	0	13	5	0.15	0.21	0.254
MTN	Urban	57.2	3.86	168	753	131	29	50	51	0	0.43	0.57	0.267
NENG	Rural	17.8	1.23	32	164	38	17	0	21	0	0.13	0.18	0.321
NENG	Urban	30.7	2	58	371	72	14	35	23	0	0.23	0.3	0.347
PAC-CA	Rural	10.9	0.723	24	79	17	5	0	10	1	0.081	0.11	0.249
PAC-CA	Urban	119	7.76	360	1362	227	10	106	110	0	0.89	1.2	0.247
PAC-NL	Rural	10.5	0.722	28	79	23	12	0	9	1	0.078	0.11	0.227
PAC-NL	Urban	29.8	1.98	81	347	57	4	23	29	0	0.22	0.29	0.266
SAT-FL	Rural	6.92	0.485	21	69	13	4	0	8	0	0.052	0.072	0.233
SAT-FL	Urban	56.2	3.81	93	736	110	6	47	55	0	0.42	0.57	0.403
SAT-NL	Rural	64.7	4.56	140	570	162	94	0	63	4	0.48	0.68	0.277
SAT-NL	Urban	110	7.33	300	1277	209	26	68	113	0	0.82	1.1	0.266
WNC	Rural	35.6	2.39	103	294	78	38	0	40	0	0.27	0.36	0.224
WNC	Urban	42.6	2.85	105	570	95	20	37	38	0	0.32	0.42	0.304
WSC-NL	Rural	19	1.2	45	178	26	0	4	22	0	0.14	0.18	0.267
WSC-NL	Urban	27.3	1.78	81	350	57	2	34	21	0	0.2	0.26	0.262
WSC-TX	Rural	26.5	1.82	62	210	56	28	0	25	2	0.2	0.27	0.251
WSC-TX	Urban	78.8	5.33	225	938	150	18	48	83	0	0.59	0.79	0.260

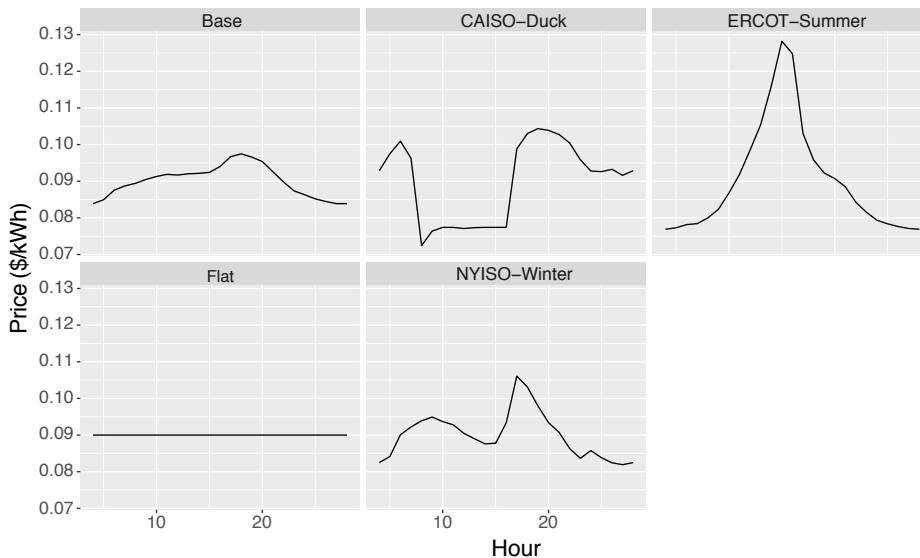


FIGURE 4 Diurnal electricity price used in price shape experiment. Shapes are derived from 2017-2018 wholesale marginal pricing data from various Independent System Operators. Each profile has an average price of \$0.09/kWh.

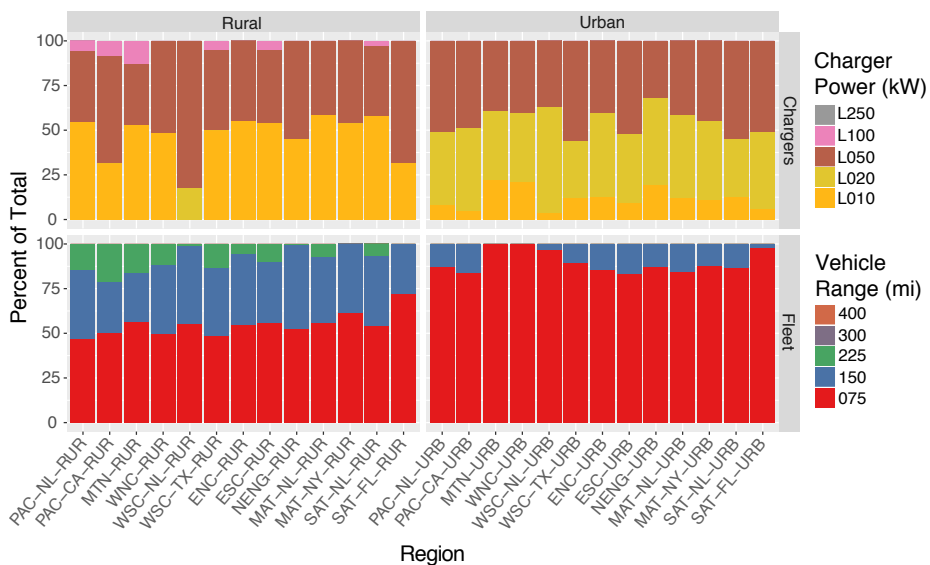


FIGURE 5 Optimal distribution of fleet vehicles and charging infrastructure for base scenario.

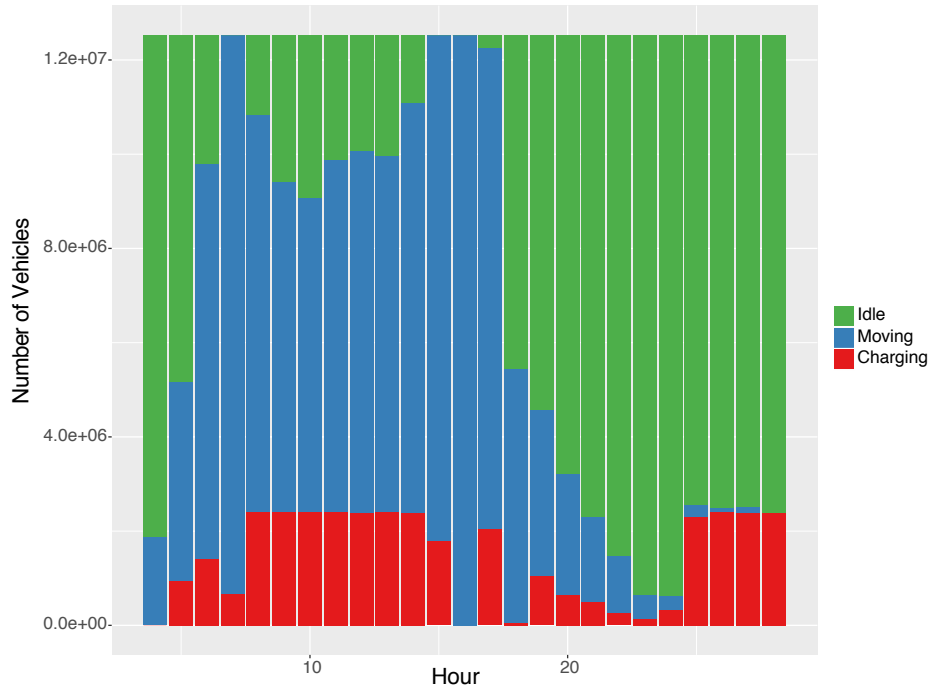


FIGURE 6 Vehicle dispatch by hour between moving (i.e. serving mobility demand), charging, or sitting idle.



FIGURE 7 Aggregate energy stored in national fleet batteries by vehicle range by hour of day.

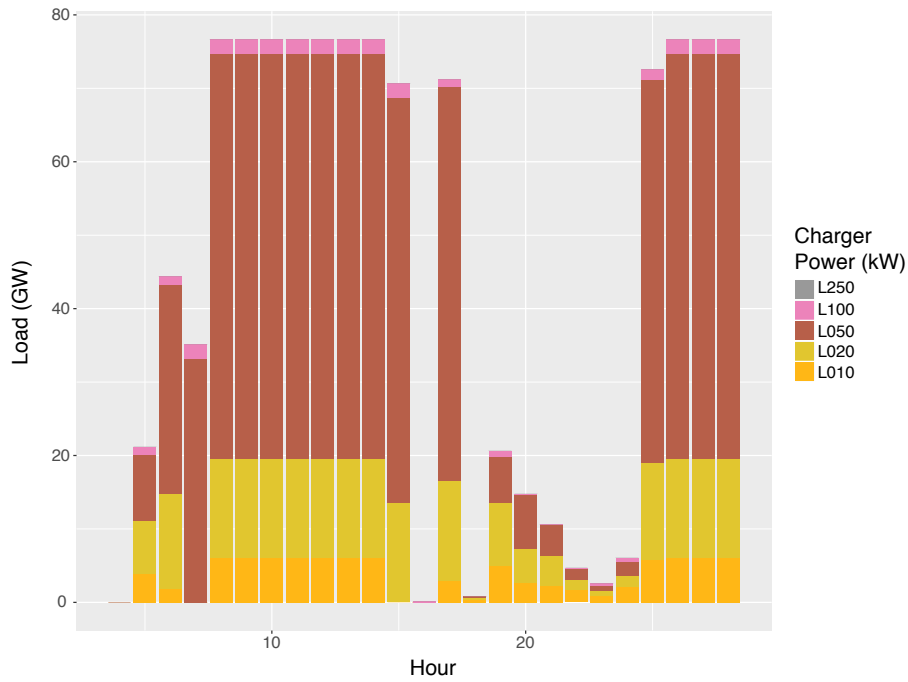


FIGURE 8 Charging profile of national fleet by charger power capacity.

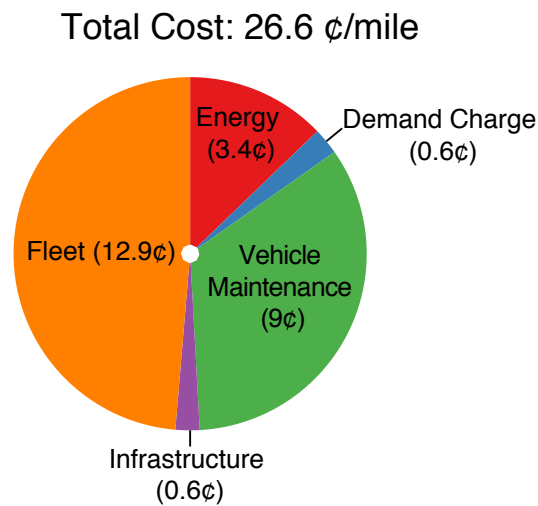


FIGURE 9 Cost per mile by cost category for the base scenario.

1 Illustrative Sensitivities

- 2 We conducted several sensitivity experiments to assess the response of the optimal solution to key
- 3 model inputs and assumptions.

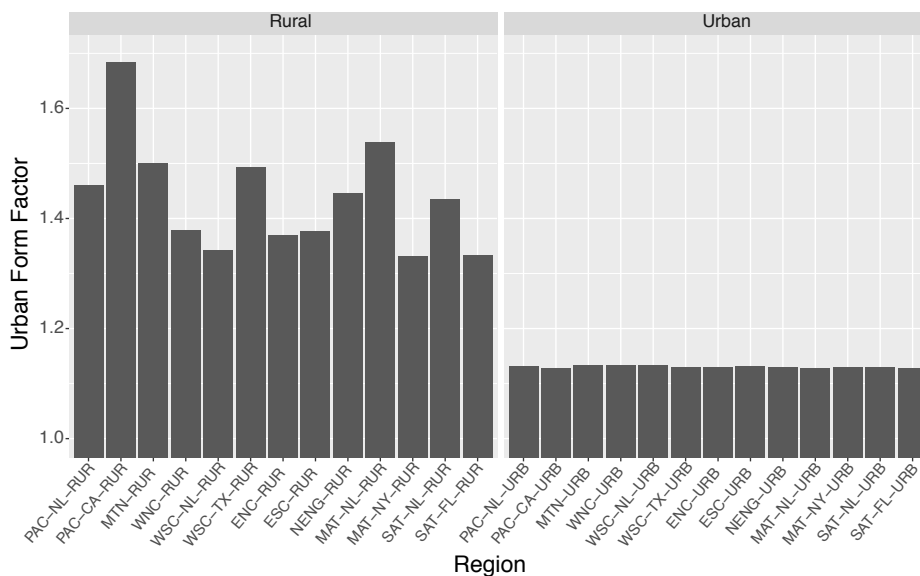


FIGURE 10 Urban form factor (μ_r) for each region in the base scenario.

1 *Ride Sharing*

2 The first analysis involves varying the assumption of ride sharing, as this is a parameter that is
 3 widely recognized to have a dramatic impact on system outcomes. In Figure 11 the fleet and
 4 charger composition are shown for each scenario in the experiment. Because the sharing factor is
 5 a simple multiplier on demand, the optimal solution is identical in all respects except that many
 6 decision variables are simply scaled. Across all metrics of interest (fleet size, charger requirements,
 7 electricity demand, etc.) the solution is scaled in proportion to the sharing factor.

8 While these results are uncomplicated, they do highlight the power of sharing in a future
 9 transportation system. It has immense potential to improve the efficiency of mobility and to de-
 10 crease the negative impacts. Because sharing is not evenly distributed, we will assess how the
 11 sharing factor changes across regions and time in future research.

12 *Battery Cost*

13 In a separate sensitivity, we varied the cost of batteries (Figure 12). Higher cost batteries lead to
 14 a fleet with shorter range vehicles and vice versa. These shifts cause the total battery capacity
 15 procured for the fleet to vary from the base solution by +68% for \$25/kWh batteries and by -4%
 16 for \$250/kWh batteries. In other words, expensive batteries incentivize a reduction in the total pur-
 17 chase of batteries which can only be achieved by distributing them among shorter range vehicles.
 18 The total fleet size also increases very slightly with higher battery costs (< 1%); this we attribute
 19 to the increased need for some vehicles to charge during the afternoon rush. Conversely, at lower
 20 battery costs — less than or equal to the base cost of \$150/kWh — when the fleet mix includes
 21 longer range vehicles, the need for charging at 4pm vanishes.

22 The change in fleet composition also changes the composition of the charging infrastruc-
 23 ture. There are three distinct trends, from \$25-75/kWh, there is a substitution of 20kW for a
 24 combination of 50kW and 10kW chargers. From \$75-150/kWh, the 50kW chargers increase at the
 25 expense of lower power charging. From \$150-250/kWh, 100kW chargers enter the solution, com-

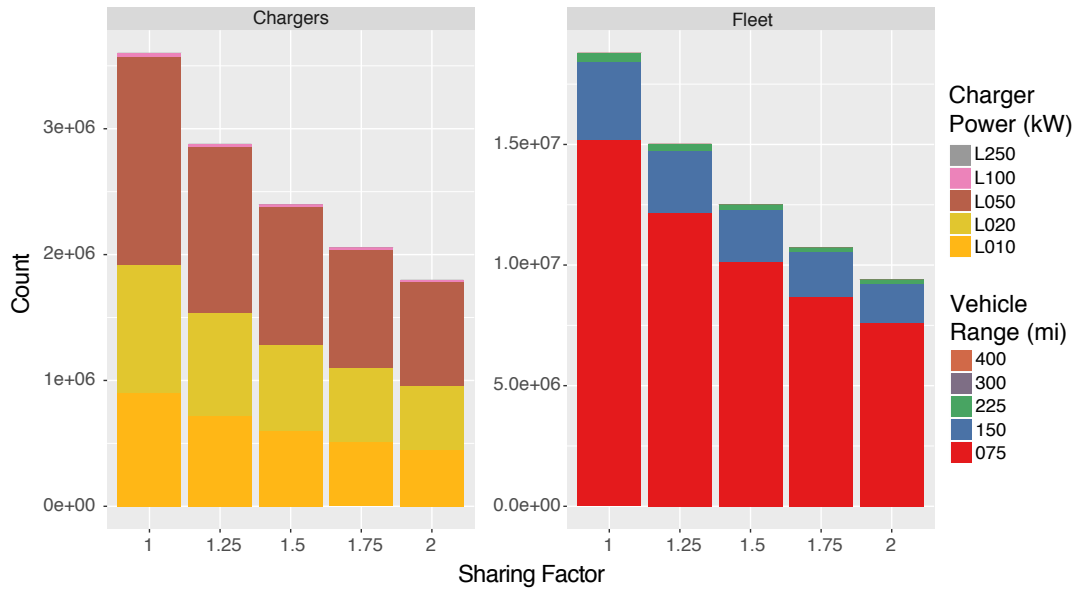


FIGURE 11 National charging infrastructure (left) and fleet composition (right) requirements for varying assumptions on sharing factor σ_d (x-axis).

- 1 posing 5-10% of the total power capacity of the infrastructure. In general, as the fleet shifts toward
- 2 shorter-range vehicles, there is an increased reliance on higher power chargers. Faster chargers
- 3 allow lower range vehicles to be quickly recharged and utilized in situations where a longer-range
- 4 vehicle could have simply continued driving.

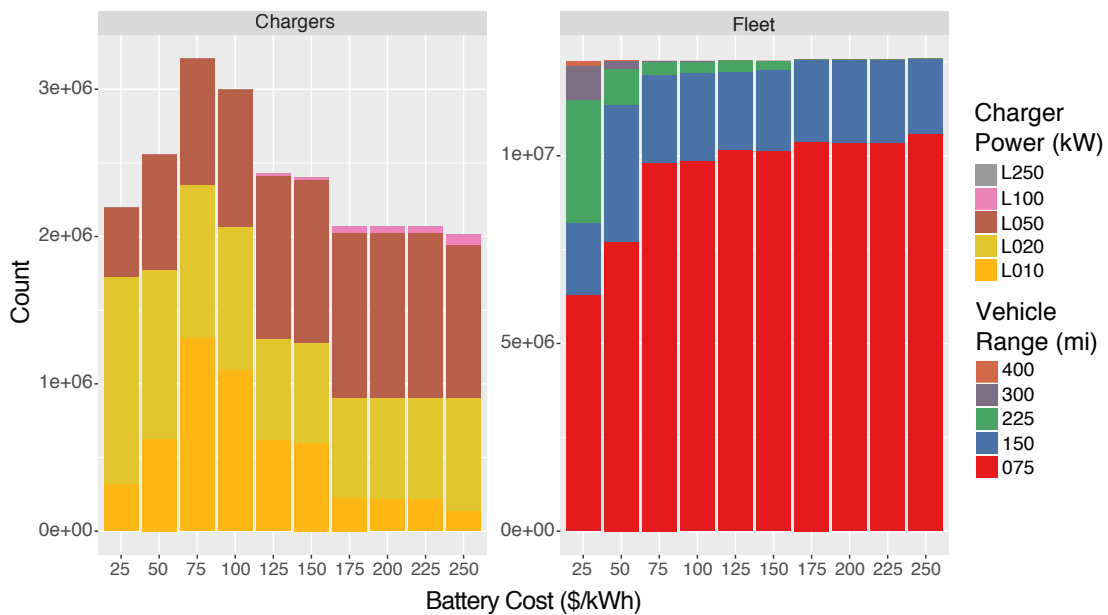


FIGURE 12 National charging infrastructure (left) and fleet composition (right) requirements for varying assumptions on battery cost (x-axis).

1 *Price Shape*

2 Finally, we explored the impact of the shape of daily electricity price profile. The scenarios are
 3 illustrated in Figure 4. The result of these different price scenarios on the aggregate charging
 4 profile are shown in Figure 13.

5 Across all scenarios, the charging profile in the first half of the day is almost identical but
 6 varies in instructive ways in the second half of the day, after the 4pm mobility peak. In the flat
 7 pricing scenario, charging never returns to the maximum during the rest of the day, indicating
 8 that there is no binding constraint on when the vehicles charge in the absence of price variation.
 9 These two results support the general conclusion that across all scenarios, charging in the first
 10 half of the day is largely dispatched to supply mobility and charging in the second half of the
 11 day is largely dispatched to minimize energy costs. For the remaining price scenarios, the price-
 12 responsive charging follows common sense patterns, avoiding the highest cost hours in favor of the
 13 lowest cost.

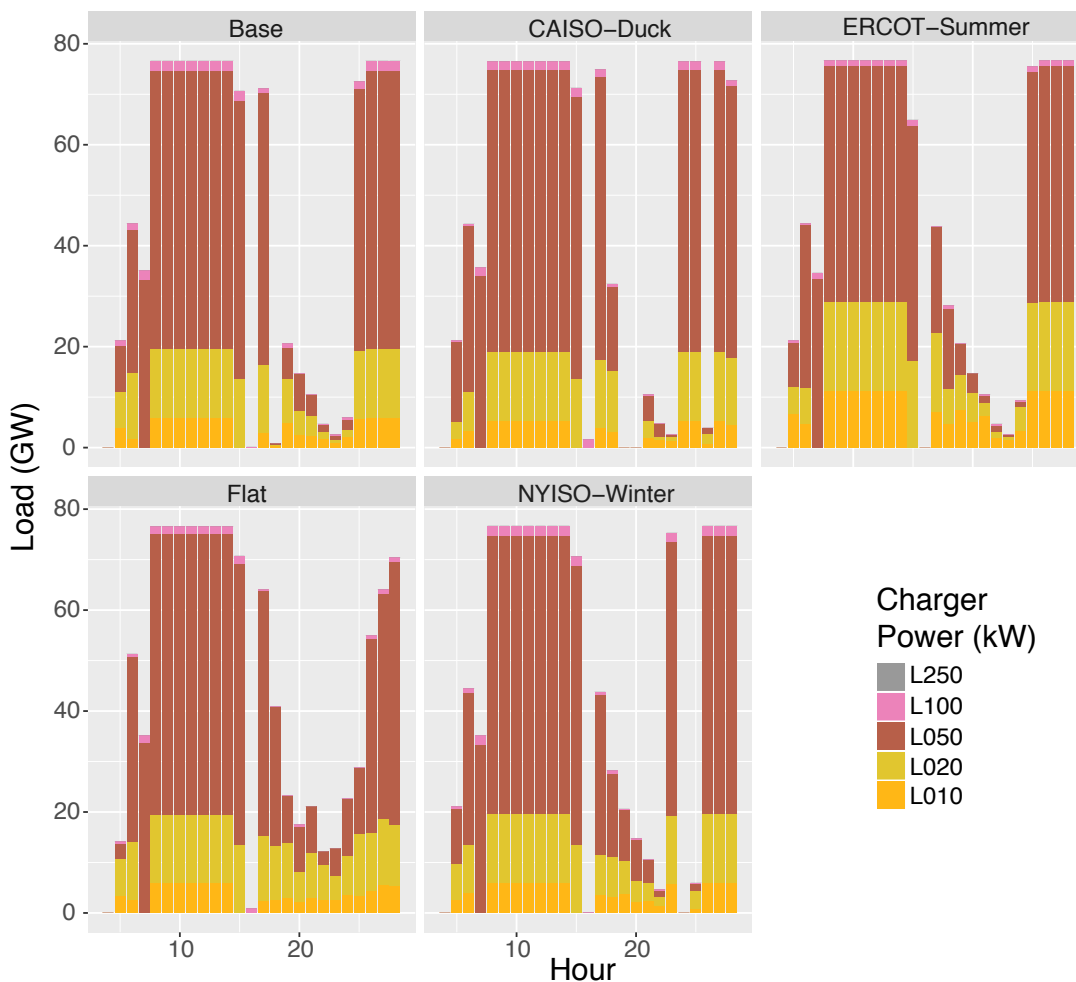


FIGURE 13 Resulting charging profile of national fleet by power capacity for various price assumptions.

1 CONCLUSION

2 We have formulated a quadratically constrained, quadratic programming problem designed to
3 model the requirements of SAEVs at a national scale. We treat the size of the SAEV fleet and
4 the necessary charging infrastructure as decision variables, allowing for heterogeneous vehicle
5 ranges and charger levels. The model minimizes operational costs by choice of the timing of fleet
6 recharging while requiring that mobility demand be served and energy conservation be maintained.
7 Planning costs are simultaneously minimized by amortizing the cost of the fleet and charging in-
8 frastructure to a daily time period.

9 In our base scenario solution, we find that all mobility in the United States currently served
10 by 276 million personally owned vehicles could be served by 12.5 million SAEVs at a cost of
11 \$0.27/vehicle-mile. The energy requirements for this fleet would be 1142 GWh/day (8.5% of 2017
12 U.S. electricity demand) and the peak charging load 76.7 GW (11% of U.S. power peak).

13 The following tasks and model improvements remain for future research:

- 14 • Increase the number of days simulated to capture day to day and seasonal variability.
- 15 • Conduct further sensitivity analysis around regionally distinct pricing scenarios.
- 16 • Couple the model to a regional scale model of power generation, simultaneously mini-
17 mize the cost of the mobility system with the cost of generating power.
- 18 • Add temporal overheads associated with charging and vehicle maintenance.
- 19 • Model heterogeneous battery lifetimes based on simulated cycling.
- 20 • Include other forms of transportation electrification (personally owned and medium/heavy
21 duty vehicles).
- 22 • Investigate heterogeneous sharing and include in the model.
- 23 • Investigate variability of urban form factor by trip distance and time of day.
- 24 • Investigate variation in the peak electricity demand over different days or seasons.

25 AUTHOR CONTRIBUTION STATEMENT

26 The authors confirm contribution to the paper as follows:

- 27 • Study conception and design: C. Sheppard, G. Bauer, B. Gerke, J. Greenblatt, A. Jenn,
28 A. Gopal
- 29 • Data collection: C. Sheppard, G. Bauer, B. Gerke
- 30 • Model development and implementation: C. Sheppard (optimization model), G. Bauer
31 (GGB model)
- 32 • Analysis and interpretation of results: C. Sheppard, G. Bauer, B. Gerke, J. Greenblatt, A.
33 Jenn
- 34 • Draft manuscript preparation: C. Sheppard, G. Bauer, B. Gerke, J. Greenblatt
- 35 • Authors reviewed the results and approved the final version of the manuscript

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